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Sparse representation for image restoration

[1]D. Khalandar Basha1, [2] Dr. T. Venkateswarlu
[1]Asst. Professor, Department of ECE, Institute of Aeronautical Engineering, Dundigal, Hyderabad.
[1]Research Scholar, Department of ECE SVU College of Engineering,
[2]Professor, Department of ECE SVU College of Engineering, Sri Venkateswara University, Tirupathi

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Abstract:
Picture reclamation plans to reestablish the photograph from the debased photograph. The photograph debasement is an immediate end result of expansion of commotion whilst image is catching. Explores proposed distinctive calculations to reestablish the photograph. In this paper the photograph is blanketed with Gaussian clamor of numerous commotion degrees. The contribution for the proposed framework is a debased photograph. The image is partitioned into covered patches and the similar instance patches are accumulated. These patches are set as particles inside the word reference. On the off hazard that the patches are taken into consideration over lapping kind the scale of phrase reference is more. The complete picture is prepared to a lexicon with each phase for an instance. For the reestablished photo restore of a window is searched for scarcely any first-class fixes of comparative instance in the lexicon. For reestablishing the image each close by and non-neighborhood sparsity is checked. The reclamation trouble is characterised with regularization phrases, one is to find out nearby likeness and different time period is for non-community similitude. For illuminating regularization terms based photo reclamation trouble utilizing Split-Bregman calculation. The productivity of the calculation is testicles with feature pix like cameraman, Lena, Barbara, House and parrot. The commotion is considered is Gaussian clamor with numerous clamor ranges. The parameters are evaluated are suggest rectangular blunder, root suggest square mistake, PSNR and FSIM. The results are contrasted and commonplace strategies NCSR, TVMM and so on.

Keywords:*Image restoration, noise, sparse representation, patch, regularization term.*

I. INTRODUCTION

Image restoration is process of reconstructing the original image from the degraded image. The image is degraded because of presence of noise in the image while capture the image or due transmission. The noise is added because of sensor inadequacy, low brightness or errors during transmission. The noise present in an image may be additive or multiplicative type. As the type of noise and amount of noise induced in image is always an unknown, the problem of image restoration is a challenging for researchers [1 -4] to eliminating the noise. The noise can be Gaussian type, salt – pepper type or speckle type.

Let consider an image x and y is the degraded image. Then y is represented as with addition of noise as

$$y = Hx + \eta \qquad (1)$$

The matrix H represents non invertible linear degradation operator [5-6]. As noise is unknown, the fidelity term is given by

$$\arg min_x \frac{1}{2} ||Hx - y||_2^2 \qquad (2)$$

By adding image prior information to regularization the minimization function for image restoration is given by

$$\arg min_x \frac{1}{2} ||Hx - y||_2^2 + \lambda\varphi(x) \qquad (3)$$

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Here φ(x) is regularization term and λ is Lagrange multiplier which regularization parameter. The efficiency of the image restoration problem is depends on regularization term φ(x). Many conventional algorithms are proposed for optimized regularization problems. [7 - 9].

To solve image restoration problem (3), Let us consider the regularization term is $l_0$then the optimization problem is given by

$$min_x \; ||x||_0 \quad \text{such that } ||Hx - y||_2^2 \leq \delta \qquad (4)$$

The δ is threshold value i.e. acceptable error. The solution to the problem (4) is sparse representation of the original image. Then the denoised output is

$\hat{y} \; = H\hat{x}.$

The term H is dictionary affects the image restoration problem. Further improvements are took place by adding variance to each non zero coefficient in the sparse representation. The modified Basic Pursuit is redefined as

$$min_x \quad \lambda||Wx||_1 \; + \frac{1}{2}||Hx - y||_2^2 \qquad (5)$$

Where W is a matrix contains the variance. In these two methods (4) and (5) the dictionary play major role [10-11]. These methods are global methods for solving image restoration. To overcome this drawback local processing methods are formulated. The learning dictionary are framed by dividing the image into patches of small size. These patches are used train the dictionary.

II.LOCAL MODELING

In local modeling instead of considering the entire image at a time. The image is divided into patches of size 3x3, 5x5, 7x7 or 9x9. All these patches are sparse in nature. In local model the dictionary is learned from patches. Here the patches can be considered as overlapped patches and non-overlapped patches. The algorithm for local processing in presented in Table 1.

Table 1: Local Model of Sparse Representation for image restoration

1. Consider a patch of size $\sqrt{n} \; x \; \sqrt{n}$ with each pixel of the image as center of the patch.
2. For each patch
   a. Compute $\widehat{p_i} = \; H^T x_i$, where x_i is a patch
   b. Apply threshold
   c. Reconstruct the patch with $H\widehat{p_i}$
3. By combining the reconstructed patches, the reconstructed image can be obtained.

These local modeling algorithms are modified by making use of learning redundant dictionaries for image patches by changing threshold method by OMP or BP. The sparse representation of image patches is updated using either MOD or K-SVD method. Reparative execution of these two steps learns the dictionary algorithm on noisy patches. The K-SVD method depends on learning the dictionary on the degraded images. Still improvement for the K-SVD is by adaptive nature for learning dictionary per each patch by its position. For each pixel the dictionary is from their neighborhood pixels. By this method non local means (NLM) algorithm is proposed [12]. NLM performs a local weighted average. The performance of the NLM depends on weights. The bilateral filter method uses patch of size 1x1. In block-Matching 3d (BM3D) [13] method is same as NLM, it finds a set of patches throughout the image. These patches are stacked into 3D. This is repeated for each and every pixel of the image. The weight of the patches is inversely proportional to the number of non-zeros in the patches in thresholding.

The unconstrained problem is converted to constraint problem by Split – Bregman algorithm. The algorithm is explained in Table 2. Consider a problem

$$\hat{u} = \arg min_x \; ||Wu||_1 + \frac{\lambda}{2}||y - Hu||_2^2 \qquad (6)$$

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Table 2: Split – Bregman iterative algorithm

1. The problem (6) can be written as

$$\hat{x} = \arg min_x \, ||d||_1 + \frac{\lambda}{2}||y - Hx||_2^2$$

$$s.t. \quad d = Wx \qquad (7)$$

2. The unconstrained problem of (7) is

$$\hat{x} = \arg min_x \, ||d||_1 + \frac{\lambda}{2}||y - Hx||_2^2 + \frac{\beta}{2}||d - Wx||_2^2 \qquad (8)$$

3. The problem (8) iteratively solve the sub problems

$$(x^{k+1}, d^{k+1}) = \arg min_{x,d} |d|_1 + \frac{\lambda}{2}||\, y - Hx||_2^2 + \frac{\beta}{2}||d - Wx - b_d^k||_2^2 \qquad (9)$$

$$b_d^{k+1} = b_d^k + Wx^{k+1} - d^{k+1} \qquad (10)$$

III. PROPOSED SYSTEM

In this paper the image restoration is done by defining two regularization terms. These regularization terms for finding both local and non-local self-similarities. By inclusion of these terms the image restoration problem is defined as

$$\arg min_x \frac{1}{2} \, ||Hx - y||_2^2 + \mu_1 \varphi(x) + \mu_2 \phi(x) \qquad (11)$$

The term$\varphi(x)$ is regularization term for local similarity and the term $\phi(x)$ is for non-local similarity. The local similarity is find by l_1 – norm which is derivative function. This is used for restoring edge information [14-15]. The non-local similarity function uses l_1 – norm to find the sparsity for image restoration using non local similarity feature [16]. μ_1, μ_2 are regularization parameters. They are Lagrange multipliers.

In the proposed system the patches are considered of size 8x8 with overlap patches. These patches are used to train the dictionary. The similar kind of patch patterns [3] are placed in a column. The size of the dictionary depends on the patterns in the image. For each patch to restore it will compare the atoms of the dictionary and selects few best patches which are close the test patch pattern. After finding similar patches the estimated coefficients are considered by applying SVD [17] for sparse approximation.

The flow of the algorithm is as follows:

Step1: Consider a clean image of size 256x256. Then add Gaussian noise which will give degraded image.

Step2: Apply first derivative for the image in both spatial domains.

Step3: Update the adaptive dictionary. By training the dictionary of similar patterns.

Step4: For each pattern of degraded image search for best suitable patches from the dictionary.

Step5: For the patches of similar pattern estimated coefficients, find the coefficients with non-zero elements.

Step6: Repeat the process for entire image.

Step7: Evaluate the performance of the algorithm by estimating the parameters like mean square error, root mean square error, PSNR and FSIM.

IV RESULTS AND DISCUSSIONS

The proposed restoration algorithm is implemented using MATLAB. The performance of the algorithm is compared with some conventional methods. The image considered for testing the algorithm are shown in Fig 1. The performance is estimated with the parameters like MSE, RMSE, PSNR [18] and FSIM. In the experimental setup the regularization parameters considered are 0.1, 0.015 and 0.02. The parameters are estimated for all these three cases. It shows better results for 0.01 case.

Fig 1: Test images considered for testing the algorithm

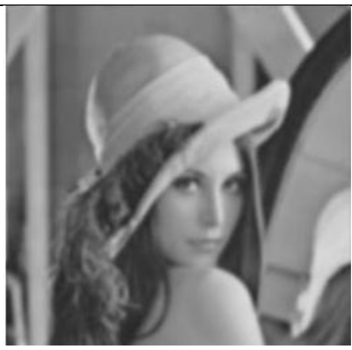
Fig 2 show the original image , noisy image and restored image of test images like cameraman, Lena, Barbara, house and parrot.

Table 1 gives the mean square error. The MSE gives deviation between original image and restored image. It is defined as squared of variation between original image and restored image. The lower the value of MSE, the more noise removed.

Table1: MSE values

μ value	0.1	0.15	0.2
Cameraman	107.412	108.437	109.646
Barbara	670.261	676.962	687.383
Lena	46.663	46.3617	46.2685
House	23.9685	23.5192	23.447
Parrot	92.216	92.5459	93.0925

Table 2 gives the RMSE values. It the square root function of MSE value. This is also used find dissimilarities between original image and restored image. As lower value of MSE is preferred for image

	Original image	Noisy image	Restored image
Cameraman			
Lena			

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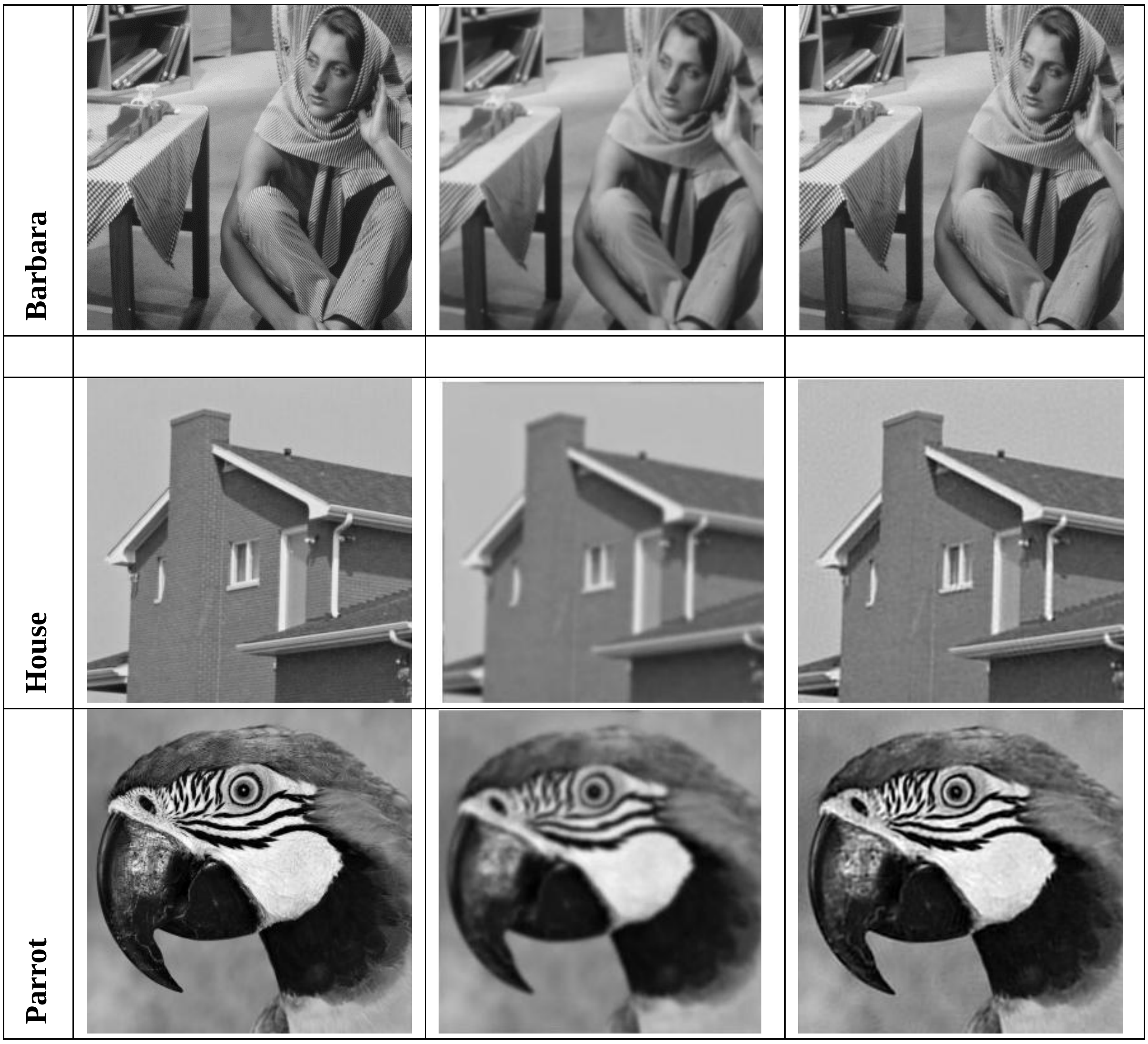

Fig 2:Original image, noisy image and restored images.

Table 2: RMSE values

µ value	0.01	0.015	0.02
Cameraman	10.364	10.413	10.471
Barbara	25.889	26.019	26.218
Lena	6.831	6.8089	6.802
House	4.8958	4.8497	4.842
Parrot	9.603	9.6201	9.6484

PSNR is peak signal to noise ratio. It is calculated as log of the ratio of square of max value to MSE. The PSNR is inversely proportional to MSE so the more PSNR the more noise removal. Table 3 gives the PSNR values for different images. The quality factor for phase and gradient magnitude is FSIM (Feature similarity Index measure) [19]. The range of FSIM is [0 1]. Table 4 gives the FSIM values of different images.

Table 3: PSNR values

µ value	0.01	0.015	0.02
Cameraman	27.820	27.779	27.731
Barbara	25.889	25.846	25.779
Lena	31.441	31.4692	31.478
House	34.334	34.417	34.43
Parrot	28.483	28.4672	28.4417

Table 4: FSIM values

µ value	0.01	0.015	0.02
Cameraman	0.8993	0.9007	0.9013
Barbara	0.9755	0.9757	0.9757
Lena	0.9440	0.9456	0.9463

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House	0.9421	09421	0.9415
Parrot	0.9278	0.9289	0.9290

IV. CONCLUSION

Picture rebuilding is the way in the direction of reestablishing the first picture from corrupted image. The photograph is corrupted resulting from commotion introduced to the photo. The expulsion of clamor within the photograph is trying in photo reclamation. In this paper the calculation for picture reclamation is carried out. The badly situated picture reclamation is communicated in (three). For reestablishing two regularization phrases are taken into consideration on this paper. Nearby self-likeness and non-community comparability. The self-likeness is integrated as the considerable majority of the photograph have same pressure of community pixel. The non-close by likeness is applied as the example are rehashing within the image. The insufficient idea of photograph on non-region sparsity is implemented for reestablishing. For testing the calculation infrequently any commonplace images are taken into consideration, they're cameraman, Lena, Barbara, residence and parrot pics. The commotion brought to the photograph is Gaussian type. Thealgorithm is attempted with variety in regularization parameter. The parameters evaluated are MSE, RMSE, PSNR and FSIM. The accomplished calculation is tried with regular techniques. For future paintings, the calculation is tried for evacuation salt-pepper commotion with the aid of differing the regularization terms.

REFERENCES

1. M. R. Banham and A. K. Katsaggelos, "Computerized photograph recovery,"IEEE Trans. Signal Processing Mag., vol. 14, no. 2, pp. 24–forty one, Mar. 1997.
2. L. Rudin, S. Osher, and E. Fatemi, "Nonlinear all out variationbased clamor expulsion calculations," Phys. D., vol. 60, pp. 259–268,1992.
3. A. Chambolle, "A calculation for all out variety minimizationand packages," J. Math. Imaging Vis., vol. 20, pp. 89–97,2004.
4. Khalandar Basha, D.,Dr. T Venkateswarlu, "calculations on scanty portrayal". Global diary of building and innovation, [s.L.], v. 7, n. Four.36, p. 569-573, dec. 2018. Doi:http://dx.Doi.Org/10.14419/ijet.V7i4.36.24139
5. H. Takeda, S. Farsiu, and P. Milanfar, "Piece relapse for photograph getting ready and reproduction," IEEE Trans. On ImageProcess., vol. 16, no. 2, pp. 349–366, Feb. 2007.
6. G. Zhai and X. Yang, "Picture activity from abnormal examples with multiscale half breed parametric and nonparametric modeling,"IEEE Trans. On Circuits and Systems for Video Technology, vol. 22, no. 11, pp. 1554–1563, Nov. 2012.
7. J. Bioucas-Dias and M. Figueiredo, "any other TwIST: Two-advance iterative shrinkage/thresholding calculations for photograph rebuilding," IEEE Trans.Image Process., vol. Sixteen, no. 12, pp. 2992–3004, Dec. 2007.
8. M. Afonso, J. Bioucas-Dias, and M. Figueiredo, "Quick photograph recoveryusing variable parting and obliged advancement," IEEE Trans.Image Process., vol. 19, no. 9, pp. 2345–2356, Sep. 2010.
9. T. Goldstein and S. Osher, "The cut up Bregman calculation for L1regularized problems," SIAM J. Imag. Sci., vol. 2, no. 2, pp. 323–343,Apr. 2009.
10. M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: A calculation fordesigning overcomplete phrase references for meager portrayal," IEEETrans. Signal Process., vol. 54, no. 11, pp. 4311–4322, Nov. 2006.
11. K. Engan, S. O. Aase, and J. H. Hakon-Husoy, "Technique for optimaldirections for outline plan," in Proc. IEEE Int. Conf. Acoust., Speech,Signal Process., vol. 5. Blemish. 1999, pp. 2443–2446.
12. A. Buades, B. Coll, and J. M. Morel, "A non-nearby calculation for imagedenoising," in Proc. Int. Conf. CVPR, Jun. 2005, pp. 60–65.
13. K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Picture restorationby scanty 3-D alternate space communitarian filtering," Proc. SPIE,vol. 6812, p. 681207, Mar. 2008.
14. A. Elmoataz, O. Lezoray, and S. Bougleux,

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January-February 2020
ISSN: 0193-4120 Page No. 8282 - 8288

"Nonlocal discrete regularizationon weighted charts: A shape for image and manifoldprocessing," IEEE Trans. Picture Process., vol. 17, no. 7, pp. 1047–1060,Jul. 2008.
15. M. Jung, X. Bresson, T. F. Chan, and L. A. Vese, "NonlocalMumford–Shah regularizers for shading picture reclamation," IEEE Trans.Image Process., vol. 20, no. 6, pp. 1583–1598, Jun. 2011.
16. W. Dong, L. Zhang, G. Shi, and X. Li, "Nonlocally unified sparserepresentation for picture reclamation," IEEE Trans. Picture Process.,vol. 22, no. 4, pp. 1620–1630, Apr. 2013.
17. M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: A calculation fordesigning overcomplete lexicons for scanty portrayal," IEEETrans. Signal Process., vol. 54, no. Eleven, pp. 4311–4322, Nov. 2006.
18. D. Khalandar Basha, Dr. T Venkateswarlu, "Straight Regression Supporting Vector Machine and Hybrid LOG Filter-Based Image Restoration", Journal of Intelligent Systems, 20180492, DOI: https://doi.Org/10.1515/jisys-2018-0492.
19. L. Zhang, L. Zhang, X. Mou and D. Zhang, "FSIM: A Feature Similarity Index for Image Quality Assessment," in IEEE Transactions on Image Processing, vol. 20, no. 8, pp. 2378-2386, Aug. 2011. Doi: 10.1109/TIP.2011.2109730